Hybrid Template- and Model-Based ATR Formulation

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Abstract

Template-based automatic target recognition (ATR) algorithms such as the Synthetic Aperture Radar Target Location and Recognition System (STARLOS) algorithm typically use separate templates to represent target signatures for ranges of articulations, aspect, depression, and squint angles. There is a performance tradeoff between ATR accuracy and the number of templates used. We use a hybrid model/template with target models to augment a small set of target templates. The basic idea will be to determine the transformation or perturbations required to modify a given template so that it accurately represents the signature of a neighboring sensor geometry or target articulation. By incorporating a model for these perturbations into the ATR algorithm, we can reduce the total number of templates required and provide robustness to new collection geometries, obscuration, and articulation.

1. Introduction

Two of the major thrusts in the ATR area are in model based vision (MBV) and template matching (TM). Numerous algorithms have been developed following these two paradigms. Applications of these ATR approaches include the DARPA Moving and Stationary Target Acquisition and Recognition (MSTAR) program which uses the MBV approach, and the DARPA Semi Automated Image Processing (SAIP) and Army STARLOS programs which employ a TM approach.

Both algorithm paradigms address some serious difficulties in recognition of targets in high clutter from synthetic aperture radar (SAR) data. SAR signatures are nonliteral and change very rapidly as a function of sensor/target geometry. Other effects, such as layover, obscuration, and concealment through nets, etc., only serve to complicate matters.

The overall goal of each paradigm is identical: associate a prescribed hypothesis concerning target type and state to a received piece of data. We will have N hypotheses $H_0, H_1, \ldots, H_n, \ldots, H_N$. The hypotheses under test are

$$\begin{aligned} H_0 &: \text{ clutter,} \\ H_{\underline{n}} &: \text{ target in state } \theta_{\underline{n}}. \end{aligned}$$

The "state" of the target is $\theta_{\underline{n}}$=[target class k, relative geometry ϕ_l, target articulation β_m, and amount of obscuration ψ_n]. The variable $\underline{n}$ is a four-dimensional vector index in state space $[k, l, m, n]$. Examples of target classes are k=[M1 tank, T72 tank, M35 truck, etc.]. Relative geometry is based on target pose (aspect) and collection geometry (squint, depression angles). The target articulation is based on the state of doors, hatches, and relative angles of turrets, trailers, and other reconfigurable target components. Finally, obscuration accounts for shadowing and layover effects from adjacent clutter such as tree-lines, and some deliberate camouflage and concealment techniques.

The hypothesis chosen is based on the minimum distance, d, between a set of features $\underline{f}(X) = [f_1(X), f_2(X), \ldots, f_M(X)]^t$ derived from the data under test, X, and a reference function vector $\underline{R}_{\underline{n}}$

$$\min_{H_{\underline{n}}} d(\underline{f}(X), \underline{R}_{\underline{n}}) < \gamma. \quad (1)$$

Each reference function vector is tied to a specific hypothesis $H_{\underline{n}}$. That reference function vector which is closest to the input data and is "close enough" (below a threshold, γ) determines which hypothesis the algorithm reports.

For the template-based approach, we would use representative input data to form a representative exemplar (i.e., $\underline{f}(X) = \tilde{X}$). The reference function would then be a spatial gray-level template. Conversely, the model-based approach uses features derived from an abstract target representation. The reference function vector in this case consists of discrete representative features derived from a mathematical target signature model which are matched against corresponding features computed from the input sensor data.

Both paradigms offer a coarse-to-fine approach to finding the best hypothesis for the data. Both approaches have a similar front-end: a prescreening and indexing stage. The prescreening stage attempts to differentiate between H_0: *clutter only,* from the hypothesis H_{tgt}: *target present.* Note that $H_1, \ldots, H_N \in H_{tgt}$. Similarly, the indexer subdivides the hypothesis space H_{tgt} into coarse subspaces H_n^{index} such as "tank at orientation $30^o - 40^o$." This discussion addresses the operations after the indexing stage.

Each paradigm has unique strengths and weaknesses, along with philosophical conflicts. The model-based approach accommodates obscuration and articulation through the models of the targets. This allows for a finer grained sampling of the hypothesis space of interest. The template-based approach is based on actual collected signatures. There is no question as to whether the collected data accurately portray the signature of interest. However, the template-based approach cannot densely sample the entire hypothesis space of interest. We propose a hybrid approach that combines the best features of both.

2. Model-Based Approach

A model-based ATR recognizes targets by matching features extracted from the unknown signature against predictions of those features generated from mathematical models of the sensing process and candidate target geometries [1]. Note that the matching is done on a feature level which may or may not encompass the actual signature of the target itself. Examples of features can be found in the literature [2]. The backbone of the model-based paradigm is a hypothesis-and-test (HAT) approach whereby a target type/state is hypothesized, the appropriate feature set extracted from models, the features matched, and a likelihood score determined. This process is iterated until the hypothesis with the highest likelihood is decided upon.

The overall process flow of the MSTAR model-based ATR algorithm is shown in figure 1. The heart of the MSTAR algorithm is the Predict, Extract, Match, and Search (PEMS) modules. The PEMS modules perform the HAT functions. The Search module controls the PEMS loop by accumulating evidence and controlling the reasoning process. Search invokes the extract module, which extracts features of interest from the input data, and the prediction module, which predicts the value of the same feature set for that target. The match module provides the computation of the distance measure between the extracted and predicted features and also the measure of uncertainty. The objective function is the likelihood function of an extracted feature set conditioned on a specific target type/pose [3].

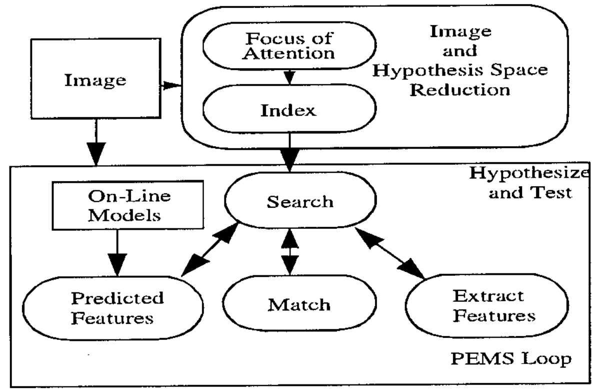

Figure 1. MSTAR model-based algorithm paradigm.

3. Template-Based Approach

In the template-based approach, a set of templates is produced from collected data and compared to the input data. These templates are representative spatial signatures of the given target hypothesis. The representative spatial signature can be a sample of the signature set at a specific geometry/state, or a linear combination of registered signatures over a range of geometries/states. The STARLOS algorithm, for example, uses a decision metric related to a mean square fitting error [4, 5], where

$$d(X, \underline{R_n}) = 1 - \frac{1}{M} \sum_{i,j} \left(\frac{\alpha X(i,j) - \mu_{\underline{n}}(i,j)}{\sigma_{\underline{n}}(i,j)} \right)^2 . \tag{2}$$

$X(i,j)$ is the image chip under test, and $\underline{R_n} = [\mu_{\underline{n}}, \sigma_{\underline{n}}]$. $\mu_{\underline{n}}(i,j)$ is a "mean image" indexed with respect to target class and geometry, $\sigma_{\underline{n}}(i,j)$ is the corresponding target signature spatial standard de-

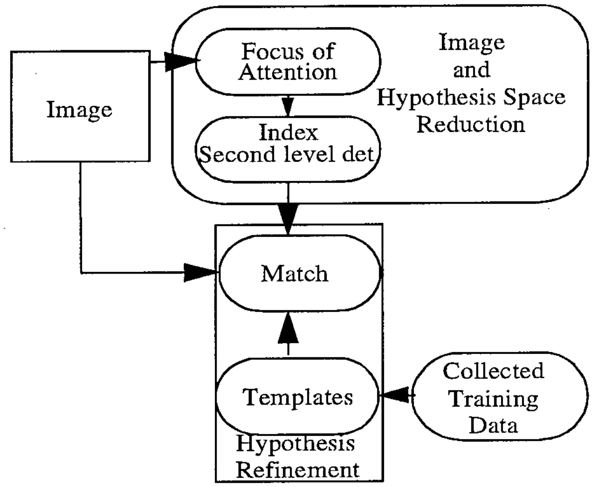

Figure 2. Template-based algorithm paradigm.

viation, and M is the number of pixels in the target chip. The template that best represents the data and has enough evidence of a match selects hypothesis $\underline{n}$. Figure 2 shows the processing flow for the template-based approach.

The mean image $\mu_{\underline{n}}(i,j)$ is produced by linearly combining registered signatures of a particular target over a local set of collection geometries. Currently, the emphasis has been on combining signatures over local target aspect. This is done to reduce the number of templates over which tests must be made. Similarly, the target signature spatial standard deviation $\sigma_{\underline{n}}(i,j)$ is formed by analyzing the pixel-by-pixel signature variability.

4. Hybrid Model/Template Approaches

The granularity of potential hypothesis space helps to differentiate between TM and MBV. Because of the requirement to generate a computationally manageable set of discrete hypotheses while spanning the large target/pose/articulation/obscuration space, the TM-based approaches must perform a coarser sampling of the hypothesis space than can be accomplished with an MBV-based approach. TM approaches offer a computational advantage, however, in that the templates are calculated offline, stored in memory, and are thus directly available for application to the decision statistic. The model-based approach, while providing a finer sampling of the hypothesis space, must reproduce a feature set indicative of the hypothesis prior to application of the decision statistic. A graphical description of this is shown in figure 3, where

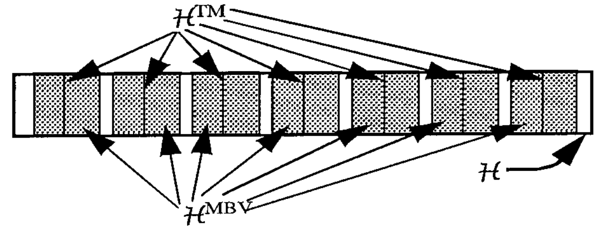

Figure 3. Sampling of the hypothesis space for the template-based and model-based methods.

$\mathcal{H}^{TM} = \{H_{\underline{n}} : \text{have templates } R_{\underline{n}}\}$, $\mathcal{H}^{MBV} = \{H_{\underline{n}} :$ can generate model-based reference functions $\underline{R}_{\underline{n}}\}$, and $\mathcal{H}$ is the space of all possible hypotheses. $\mathcal{H}^{TM} \subset \mathcal{H}^{MBV} \subset \mathcal{H}$.

The difference in sampling of the hypothesis space suggests two alternatives for a hybrid model/template approach.

4.1. TM for Fine Indexing

This approach, shown in figure 4, inserts the TM algorithm as another indexing stage to further refine the hypothesis estimates before the application of the MBV algorithm. Refined hypotheses are obtained through the template set. This reduces the number of hypotheses over which the MBV algorithm must search. The drawback for this approach is that a large template set must still be used. The added computation of this insertion may offset the advantage of not having to search over a large hypothesis space.

4.2. MBV for Template Perturbation

A more promising alternative is to employ the model-based paradigm as a means of altering the templates (reference functions) that are applied to the data. In this approach, the templates would be seen as the core signature upon which model-based distortion operators and signature changes would be made. The amended reference function would become

$$\underline{R}'_{\underline{n}'} = \mathcal{O}_{\underline{n}'}\{\underline{R}_{\underline{n}}\} + \delta \underline{R}_{\underline{n}'}, \tag{3}$$

where $\underline{n}' = \underline{n} + \delta \underline{n}$, $H_{\underline{n}} \in \mathcal{H}^{TM}$, and $H_{\underline{n}'} \in \mathcal{H}^{MBV} \notin \mathcal{H}^{TM}$. A simple starting point is to use the mean image template as the reference function (i.e., $\underline{R}_{\underline{n}} = \mu_{\underline{n}}$). The operator $\mathcal{O}_{\underline{n}'}$ would predominantly account for geometry and pose variations. This could be interpreted as a "distortion operation." The term $\delta \underline{R}_{\underline{n}'}$ changes the signature based

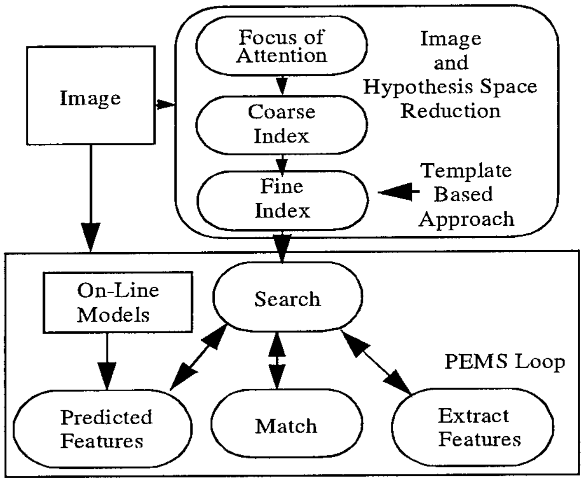

Figure 4. Straightforward hybrid model/template approach where the template approach is used as a fine indexing stage.

on articulation, obscuration, and geometry considerations. $\mathcal{O}_{\underline{n}}$ would be stored and called as required, permitting reference signature modification via the model-based predictor.

An interesting aspect of this construction is the case where fine internal detail helps determine which hypotheses to pursue. The template would be segmented into "stable" and "unstable" regions (a notion similar to the chunky template approach [5]) as a function of target state. The $|X(i,j) - \mu_{\underline{n}}(i,j)|$ term in equation (2) can rapidly determine the spatial locations of poor template fits. The hypotheses which provide $\delta\mu_{\underline{n}'}(i,j)$ over the local area are now searched.

As an example, if a template mismatch occurs in areas of known signature articulation dependence, generate model-based deformations consistent with articulation hypotheses. Alternatively, if the template signature mismatch occurs over postulated stable areas, the target class may need to be amended or specific localized scatterers (e.g., a removable external store) added or subtracted using model-based deformation to provide best fit.

The advantage of this approach is that the number of potential templates required may be reduced and the model-based search would amend the templates and fill in the gaps. In addition, the model-based approach would need to predict only the areas where the signature has changed, not the full signature, thereby reducing computational cost.

5. Discussion

We have proposed a hybrid template/model-based approach for ATR which we believe has potential to draw upon the strengths of both paradigms. One of the major stumbling blocks for any attempt to create a hybrid template/model-based system is the veracity of the models themselves. This problem is exacerbated by the notion that the model must now interact directly with the template in our construction. The other large, and unsolved, issue is the notion of scatterer correspondence between the model generated signature and the collected template.

An experiment is briefly proposed. Using a set of templates derived from collected data which are well ground truthed with respect to the specific hypothesis: (1) test the templates using MBV to see if MBV declares the correct hypothesis; (2) if not, amend the CAD model until correct declaration; 3) if yes, compare the predicted model based signature to the template itself; 4) amend the CAD model until the signatures closely match. If this experiment is successful, assume that the model will correctly predict signatures for the finer set of hypotheses.

References

[1] E. R. Keydel and W. L. Shung, "Signature prediction for model-based automatic target recognition," *Proc. SPIE: Algorithms for Synthetic Aperture Radar Imagery III*, vol. 2757, pp. 306–317, April 1996.

[2] J. Stach et. al., "A unified approach to feature extraction for model-based atr," *Proc. SPIE: Algorithms for Synthetic Aperture Radar Imagery III*, vol. 2757, pp. 294–305, April 1996.

[3] G. J. Ettinger et. al., "A probabilistic optimization approach to sar feature matching," *Proc. SPIE: Algorithms for Synthetic Aperture Radar Imagery III*, vol. 2757, pp. 318–329, April 1996.

[4] D. L. Rodkey et. al., "The starlos synthetic aperture radar target recognition and location system," *Record of the Forty-First Annual Tri-Service Radar Symposium*, vol. 268105-1-X, pp. 39–54, September 1995.

[5] J. S. Salazar et. al., "An atr approach for partially obscured targets using chunky template matching on sar data," *Record of the Forty-First Annual Tri-Service Radar Symposium*, vol. 268105-1-X, pp. 81–95, September 1995.

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